EFFECTIVENESS OF A REDD+ PROJECT IN REDUCING DEFORESTATION IN THE BRAZILIAN AMAZON

GABRIELA SIMONET, JULIE SUBERVIE, DRISS EZZINE-DE-BLAS, MARINA CROMBERG, AND AMY E. DUCHELLE

We estimate the early effects of the pilot project to Reduce Emissions from Deforestation and forest Degradation (REDD+) in the Brazilian Amazon. This project offers a mix of interventions, including conditional payments, to reduce deforestation by smallholders who depend on swidden agriculture and extensive cattle ranching. We collected original data from 181 individual farmers. We use difference-in-difference (DID) and DID-matching approaches and find evidence that supports our identification strategy. We estimate that an average of 4 ha of forest were saved on each participating farm in 2014, and that this conservation came at the expense of pastures rather than croplands. This amounts to a decrease in the deforestation rate of about 50%. We find no evidence of within-community spillovers.

Key words: Deforestation, payments for environmental services, treatment effects, quasi-experiment.

JEL codes: D12, Q23, Q57.

Tropical deforestation and degradation play an important role in anthropic emissions of carbon dioxide (CO_2), with an annual emission rate estimated at 7% to 14% of global CO_2 emissions (Harris et al. 2012; Grace, Mitchard, and Gloor 2014). For many years now, programs and policies designed to reduce tropical deforestation have featured highly on the political agenda. Afforestation and reforestation projects were included in the Clean Development Mechanism of the Kyoto Protocol signed in 1997 and a mechanism aimed at Reducing Emissions from Deforestation, known as RED, was established during the 11th Conference of the Parties of Montreal in 2005 and later expanded and renamed REDD+ to include forest degradation and the enhancement of forest carbon stocks.

Among forested countries worldwide, Brazil has been one of the main sources of global tree cover loss (Hansen et al. 2013). In Brazil, the implementation of command-and-control measures, the expansion of protected areas, and interventions in the soy and beef

Gabriela Simonet is a research scientist at the Climate Economics Chair (CEC), the French National Institute for Agricultural Research (INRA), and the Center for International Forestry Research (CIFOR). Julie Subervie is a research scientist at INRA. Driss Ezzine-de-Blas is a scientist at the UPR Forêts et Sociétés, CIRAD, Univ de Montpellier, Montpellier, France. Marina Cromberg and Amy E. Duchelle are research scientists at the Center for International Forestry Research (CIFOR), Indonesia. The data used in this article were collected by the Center for International Forestry Research (CIFOR). This research is part of CIFOR's Global Comparative Study on REDD+. The funding partners that have supported this research include the Norwegian Agency for Development Cooperation (NORAD), the International Climate Initiative (IKI) of the German Federal Ministry for the Environment, Nature Conservation, Building and Nuclear Safety (BMUB), and the CGIAR Research Program on Forests, Trees and Agroforestry (CRP-FTA), which is financially supported by the donors to the CGIAR Fund. The authors thank the men and women of the Transamazon for their hospitality and for sharing their time and perceptions, and IPAM's team for sharing their REDD+ project information with us. The authors are also grateful to the members of our field team for their outstanding collaboration. The authors further thank Erika Pinto de Paulo Pedro (IPAM), Astrid Bos (Wageningen University), Sylvain Chabé-Ferret (INRA-TSE), Nicolas Fauvet (CIRAD), Valéry Gond (CIRAD), Gwenolé Le Velly (SupAgro), Eduardo Marinho (CIFOR), Alexandre Sauquet (INRA), Raphael Soubeyran (INRA), Isabelle Tritsch (IRD), Annie Hofstetter (INRA) and audiences at a number of seminars for useful comments. The authors especially thank the editor, Travis Lybbert, and two anonymous referees for their outstanding comments and suggestions. All remaining errors are obviously our own. Correspondence to be sent to: gabriela.simonet@supagro.inra.fr.

Amer. J. Agr. Econ. 101(1): 211–229; doi: 10.1093/ajae/aay028
Published online June 18, 2018

supply chains, such as the Soy Moratorium established in 2006, have significantly curbed deforestation in the Amazon in recent years. Between 2005 and 2013, the annual deforestation rate in Brazil fell by 70% (Nepstad et al. 2014). Early access to satellite imagery, made possible by the Brazilian government's historical interest in space technologies, has been key to this success by improving the government's capacity to monitor forest cover.

Despite this overall improvement, deforestation rates have continued at 5,000–7,000 km^2 per year since 2009 (Godar et al. 2014) and increased in 2015–2016 according to the Brazilian National Space Research Institute. Furthermore, the reduction in deforestation achieved prior to 2009 can mainly be attributed to large farms, as evidence shows that small farms had a limited role in the improvements recorded during this period (Godar et al. 2014). After a decade of command-and-control regulation, it is often argued in the literature that new mechanisms targeting small landowners are required to achieve further reductions in deforestation in the Amazon (Chhatre and Agrawal 2009; Ezzine-de-Blas et al. 2011; Gebara and Thault 2013; Godar et al. 2014; Börner, Marinho, and Wunder 2015).

In this context, there has been a proliferation of subnational REDD+ initiatives in the Brazilian Amazon, which consist of a mix of incentives, disincentives, and enabling measures such as tenure clarification (Sills et al. 2014; Duchelle et al. 2014a). According to Sunderlin and Sills (2012), most subnational REDD+ initiatives are hybrids of the integrated conservation and development project (ICDP) approach and of new forest conservation approaches, such as Payments for Environmental Services (PES). Around half of the REDD+ projects implemented worldwide include a component of payment to local communities (Simonet et al. 2014). Brazil hosts some of the most emblematic subnational PES-based REDD+ initiatives, including the Bolsa Floresta Program (Börner et al. 2013; Viana et al. 2013) and Acre's State System of Incentives for Environmental Services (SISA; Duchelle et al. 2014b).

A question of primary importance is therefore: to what extent can a REDD+ project that includes a PES component contribute to avoided deforestation? There are a variety of reasons why voluntary programs like PES-based REDD+ projects may not be effective in curbing deforestation. Firstly, farmers who face the lowest costs for decreasing deforestation are the most likely to enter such a project (Persson and Alpizar 2013). As a result, the project may end up paying some farmers for doing nothing differently from what they would have done in the absence of any payment. In this case, the impact of the project may be quite small. Secondly, the impact of the project, if there is any, may be offset by negative within-community spillovers (or leakage). Negative within-community spillovers occur when the project happens to increase deforestation among non-participants through market equilibrium effects such as a change in the demand for cattle products, or when a forest-owner shifts all planned deforestation activities from a PES-enrolled plot to a non-PES-enrolled plot (Dyer et al. 2012). In the most extreme cases, for example, if some landowners use all PES payments to buy chainsaws to clear more forest for cattle pasture, negative spillovers could exceed the positive impacts of the project (Wunder 2007).

In this article, we evaluate the effectiveness of an early REDD+ project launched along the Transamazon Highway in the Brazilian Amazon. Since 2012, this REDD+ project, called Projeto Sustainable Settlements in the Amazon (PAS), has offered a mix of interventions to reduce deforestation rates, including PES and free administrative support, to 350 smallholders in several communities in the state of Pará. We estimate the impact of the project on participants, along with within-community spillovers, and use these estimates to calculate the cost of avoiding CO_2 emissions in this project. We collected land use data from a sample of 181 households in four intervention communities and four comparison communities (where the project was not offered) in 2010, as a baseline, and in 2014, that is, about two years after the beginning of the project and one year after the signing of PES contracts by local farmers. Since the final survey was run just before the payment of the first contract year, we are not able to assess how the influx of cash (through PES) into the local economy could affect deforestation rates. Therefore, any impact of the PES component could be due to the fact that enrolled participants reduced deforestation activities in anticipation of their contractual payments.

Intervention communities were not randomly selected and participants in intervention communities self-selected into the project given its voluntary nature. To deal with this issue, we use the difference-in-difference (DID) and DID-matching approaches, with evidence supporting the parallel trend assumption that both groups follow the same trend during the pre-treatment period. We estimate the impact of the project on participants and show that an average of approximately 4 hectares of forest were conserved by each participating farm compared to the counterfactual scenario with no PAS project. Although the respondents' statements about land use indicate that forest cover continues to decline in both participant and control groups after 2010, we highlight a clear break in the trend of deforestation rates among participants, which we attribute to the project. After 2010, the deforestation rate among participants decreases to 1.8% per year, which means that the project led to an approximate decrease of 50% in the average deforestation rate (compared to the counterfactual deforestation rate).[1] Moreover, we show that this decrease in deforestation occurs at the expense of pastures versus croplands. We find no evidence of within-community spillovers. Finally, we convert the impact of the project in terms of avoided CO_2 emissions and find that the project led to the reduction of around 639,000 tons of CO_2 over the first two years of implementation, resulting in a cost of 0.84 USD per avoided ton of CO_2 emissions.

Although more than 300 REDD+ projects have been implemented across the tropics (Simonet et al. 2014), impact evaluations of REDD+ projects are still scarce (Börner et al. 2013; Temu et al. 2015; Sharma et al. 2017). Research based on local perceptions highlights that households involved in REDD+ projects are generally satisfied with the results (Viana et al. 2013; Atela et al. 2015; Brimont et al. 2015), yet deforestation rates based on satellite imagery indicates that the effects of REDD+ projects on deforestation, if any, may be too small to be detectable at the community level (Bos et al. 2017). Apart from REDD+, there have been rigorous impact assessments of several PES programs for forest conservation or reforestation (see Pattanayak, Wunder, and Ferraro 2010, Samii et al. 2014, Alix-Garcia and Wolff 2014 or Börner et al. 2016 for reviews of the literature). Most studies are quasi-experimental analyses conducted in Costa Rica (Sánchez-Azolfeifa et al. 2007; Arriagada et al. 2012; Garbach, Lubell, and DeClerck 2012; Robalino and Pfaff 2013) and Mexico (Honey-Roses, Baylis, and Ramirez 2011; Scullion et al. 2011; Alix-Garcia, Shapiro, and Sims 2012; Sims et al. 2014; Alix-Garcia, Sims, and Yañez-Pagans 2015; Costedoat et al. 2015). Overall, the results of these studies suggest that the impact of PES on the average annual forest cover varies substantially across regions. Impacts are positive and significant mainly in areas where landowners face medium to low opportunity costs to participate in the projects (Börner et al. 2016), with no clear evidence of complementarity between conservation and poverty reduction goals (Samii et al. 2014). In most cases, deforestation and forest degradation are reduced but not halted. Finally, Jayachandran et al. (2017) performed an innovative randomized-controlled trial to assess the impact of a PES program for forest conservation in western Uganda, and found that tree cover declined by 4.2% during the study period in treatment villages, compared to 9.1% in control villages.

Our contribution to this literature is threefold. First, we evaluate a REDD+ pilot project, for which the impact evaluation literature is scarce, in the country with the highest deforestation globally; 984,000 hectares annually during 2010–2015 FAO (2015). Second, we draw inferences about the causal effect of the program from observational data, which is challenging (Athey and Imbens 2017). To do so, we use DID and DID-matching approaches and we provide supplementary analyses that support our choice of identification strategy. Third, we estimate not only the additionality and leakage effects of the program, but also the mechanisms through which program participants have reduced their deforestation, thus addressing a current gap in the impact evaluation literature (Börner et al. 2017).

The remainder of the article is structured as follows. The subsequent section presents the project under study and the underlying mechanisms through which the project might achieve forest conservation, that is, a theory

[1] In this article, the annual deforestation rate is calculated using the definition employed by the Food and Agriculture Organization of the United Nations and identified by Puyravaud (2003) as the most commonly used definition in the literature: $q = -\left[\left(\frac{A_1}{A_2}\right)^{\frac{1}{t_1 - t_2}} - 1\right]$, where A_1 and A_2 are the forest area at time t_1 and t_2, respectively.

of change. The next section presents the data collection process, followed by a section on the estimation methodology. The impact evaluation results are presented in the subsequent section, followed by a section illustrating our calculations regarding the costs of avoided CO_2 emissions. The last section concludes.

The PAS Project Strategy to Achieve Conservation

A Multicomponent Project

The PAS project is a REDD+ project implemented by a Brazilian non-governmental organization, the Amazon Environmental Research Institute (IPAM), which is a recognized national actor in the design and implementation of REDD+ in Brazil (Gebara et al. 2014). The PAS started in 2012 and was financed by the Amazon Fund through 2017. The participants in the project live in 13 settlements located in the municipalities of Anapu, Pacajá, and Senador José Porfírio, near the BR-230 Trans-Amazonian Highway, an area with high past and present levels of deforestation. Agricultural settlers arrived in the area in the 1970s during the early stages of the National Integration Plan for the colonization of the Brazilian Amazon. The livelihoods of small landowners in this area still depend on swidden agriculture and extensive cattle ranching, which are the two primary drivers of deforestation (Smith et al. 1996; Soares-Filho et al. 2006).

Until recently, the Brazilian Institute for the Environment and Renewable Natural Resources (IBAMA), the national environmental and legal enforcement authority, primarily targeted areas dominated by larger properties. In 2008, the government blacklisted multiple municipalities in the Amazon where deforestation was particularly prevalent. In blacklisted municipalities, law enforcement and monitoring activities were intensified, and economic sanctions and political pressures were also imposed (Assunção and Rocha 2014), successfully reducing deforestation in the targeted municipalities (Cisneros, Zhou, and Börner 2015). The three municipalities in our study were added to the blacklist in 2009 and 2012, and monitoring of small landholders in the Transamazon region intensified as of 2012.

Nevertheless, small landowners in blacklisted municipalities often continue to clear and burn forest to subsist. One objective of the PAS project was to provide technical assistance to these smallholders to help them comply with the law and engage in a without-fire agricultural transition. In fact, PAS built on a similar program called Proambiente, which was launched in 2003 and ended in 2006 due to funding cuts, after only six months of payments to local farmers (Bartels et al. 2010). Hence, an important objective of the PAS project was to build on the experience of Proambiente to facilitate a transition towards more sustainable agricultural practices by helping smallholders to intensify crop and livestock farming. We define the PAS project as a multi-component REDD+ project mixing incentives, disincentives and enabling measures, which is typical of many subnational REDD+ projects and programs globally (Sills et al. 2014; Duchelle et al. 2017). The PAS project combines four main components.

The first component is awareness-raising meetings about the Brazilian Forest Code, which requires that private properties located in the Amazon maintain at least 80% of land as forest (Legal Reserve). In some so-called Environmental Economic Zoning (or ZEE, for *Zoneamento Ecológico Econômico*) areas, such as the area of implementation of the PAS project, the Legal Reserve has been lowered to 50% to encourage economic development. The Forest Code also requires conservation of permanently protected areas (hilltops, mountain slopes, mangroves, and riparian forests) to preserve biodiversity, maintain water quality, and stabilize soils. The second component is administrative support for registration under the Rural Environmental Registry (or CAR, for *Cadastro Ambiental Rural*). The third component is support for compliance with the Forest Code through a PES scheme, while the fourth component is support for the adoption of sustainable livelihoods systems (including agroforestry, intensive cattle ranching, and fish farming) through direct cash payments and free investments in technical assistance, farm inputs (seeds, fertilizer and crop protection), equipment, and marketing of local production.

The payments offered to project participants are conditional on both forest conservation and agricultural transition toward a fire-free production system: 30% of the payment is contingent upon forest conservation on at least 50% of land as Legal Reserve; another 30% is contingent on the conservation of 15 meter-wide forest riparian zones; and the remaining 40% depends on the adoption of fire-free production systems. A minimum of 30% of forest cover is required to be eligible for payments, but only participants with at least 50% of forest cover can receive the full amount. The project thus exceeds the requirements of the 2012 amendments to the Brazilian Forest Code, which allow properties smaller than 400 hectares to maintain only the forest cover they had in July 2008. The payments provide an incentive to respect the old Forest Code in the ZEE (50% forest cover), and thus sets targets that go beyond current legal requirements. The PES component involves the creation of individual land use plans that display the spatial distribution of the new productive systems. The project indicates that the annual payment may reach a maximum of \$626 when all criteria are met, which is determined by the project proponent through annual field monitoring.[2] This was also the mean amount received through the government-sponsored Bolsa Familia social program by the households in our sample in 2014, and around 15% of the value of their agricultural production this same year. In 2014, the transition towards more sustainable agricultural systems was not yet a requirement for receiving the payment. The proportionality rule was exempted by IPAM given the delay in the implementation of the fire-free productive systems. The whole 2014 payment was thus made conditional on forest conservation only. Our analysis focuses on the impacts of the project on farm-level forest cover.

Strategy to Reduce Deforestation

The PAS project was implemented in a context that may have boosted households' participation. First, the federal policy of municipal blacklisting created a generalized fear of inspection and punishment. Farmers aware of the blacklist and vulnerable to inspection may have seen participation in the project as a way to comply with the law (Cisneros, Zhou, and Börner 2015). Second, the earlier implementation of Proambiente helped cultivate pro-environmental motivations among farmers (Ezzine-de Blas, Corbera, and Lapeyre 2015). The strategy that we use to identify the impact of PAS considers both contextual elements, as described below. Each of the three components of PAS could potentially lead to a reduction in deforestation by participants. With regard to the first component, the awareness-raising meetings might have improved farmers' knowledge of the Forest Code. Although landholders are generally aware of the existence of IBAMA, they are not always familiar with the details of the legislation and possible sanctions. Access to new information, combined with the generalized rumor of increased command-and-control in the municipalities, could foster compliance with the law (Cisneros, Zhou, and Börner 2015; Brandon et al. 2017). Regarding the second component of the Rural Environmental Registry (CAR) process, providing (publicly available) information on property boundaries and its forest cover could enhance the credibility of the command-and-control system and encourage landowners to comply with the law. A recent study, however, suggests that CAR failed in halting illegal deforestation: although small landowners in Eastern Amazonia were motivated to join state land registries and decreased their deforestation directly after entering CAR, this effect then decreased and even disappeared in the case of Pará (Azevedo et al. 2017). The third component of the project (PES) is expected to reduce deforestation because the payment value was based on the opportunity cost of maintaining forest on plots devoted to cattle ranching and crops. Participants would be paid only after compliance was verified by IPAM through field visits and satellite images. By binding contract conditionality, farmers have the incentive to protect their forests Wunder (2015). However, the impact of the payment might be heterogeneous among participants, those being closer to the threshold of 50% of forest cover having more incentives to reduce deforestation than those lying well over 50%. The influx of cash generated by the PES component could also have an impact on participants and their forests, depending on how it is used (Dyer et al. 2012). For example, Alix-Garcia et al. (2013) show that a conditional cash transfer program (not a PES scheme) called "Opportunidades", implemented in Mexico,

[2] 1,680 Reais is converted to USD by applying a conversion rate of 0.3724 (average conversion rate of Brazilian Real to U.S. dollars in 2014).

resulted in marginally higher deforestation rates in localities that received cash transfer payments due to increased local demand by participants for land-intensive goods like beef and milk.

Even without any influx of cash, several types of spillovers might be expected from the project, whether within or beyond intervention communities. Within-community spillover effects may occur when non-participating farmers in intervention communities slow deforestation on their own plots if they had the opportunity to attend awareness-raising meetings and discuss land use matters with participants. This may have convinced some of the importance of respecting the Forest Code even without the added incentive of PES. Conversely, the project may increase deforestation among non-participants if commodity prices rise locally (e.g., for cattle products) or if some participants compensate reduced production by working as a laborer in deforesting the plots of non-participant neighbors. This potential leakage of deforestation could extend beyond the borders of the intervention communities, particularly through trade.

Data

The data were collected by the Center for International Forestry Research (CIFOR), as part of its Global Comparative Study (GCS) on REDD+ launched in 2009 at 23 subnational REDD+ sites in Brazil, Peru, Indonesia, Vietnam, Cameroon, and Tanzania. To select study communities, IPAM indicated 13 communities where they had previously implemented Proambiente and planned to implement PAS. From this pool, CIFOR field teams randomly selected four intervention communities. The teams then used pre-matching methods to identify four comparison communities that were similar in terms of market accessibility, deforestation pressures, and socioeconomic factors (Sunderlin et al. 2010) (see figure A1 in the online supplementary appendix material). In all communities, interviewed households were selected randomly. In intervention communities a disproportionate stratified random sample was performed including households that had previously participated in Proambiente and those that had not (about half in each group). A total of 181 households were interviewed in two time periods. Of these, 106 households were surveyed in the intervention communities and 75 households in the comparison communities. The first survey took place in June-July 2010, before the PAS project began. The second survey took place in February-March 2014, approximately 18 months after the official start of the project. Two years after the first survey, about 10% of the households living in the intervention communities became involved in the PAS project. Because participants of Proambiente were (intentionally) over-represented in our sample, we ended up with 52 participants and 54 non-participants in 2014 (figure 1).

Our database includes variables related to the pre-project and current periods. All data was self-reported by the households during the two surveys conducted in 2010 and 2014. The forestland variable in 2008 was constructed from recall-type questions during the 2010 survey. To improve the reliability of declarative data on land use, during both surveys, each respondent was asked to draw a detailed sketch of his or her landholding. The independence between the research team in the field (CIFOR) and the project proponent (IPAM) was clearly stated at the beginning of each meeting or interview. Participants were also informed that their responses would remain anonymous. Two sections of the questionnaires are dedicated to the calculation of agriculture and forest areas, which allows us to cross-check reported land values. Moreover, we could check that the reporting of the areas under different land uses made sense over time through clarifying any inconsistent values with respondents.

A potentially important caveat in our data is the extent to which respondents might have under-declared their actual deforestation. To cross-check the validity of self-reported clearing among participants, we used remotely-sensed land use data for 2014 generated by IPAM for a representative sample of 157 PAS participants. These data are available in Pinto de Paulo Pedro (2016) and are based on analysis of LANDSAT 8 images.[3] The author calculated a mean forest cover (primary and secondary) of 67% on an average total

[3] IPAM technicians paid special attention to the issue of clouds and cloud shadows: they used a specific method to reinterpret cloud-covered areas and, when this was not feasible, they went to the field to verify the land cover in question.

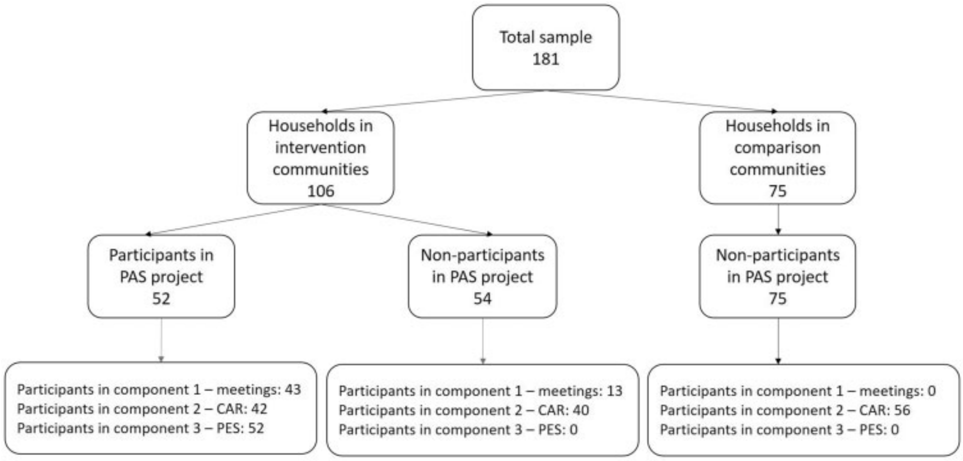

Figure 1. Sample composition

farmland area of 78.6 ha. This matches well with the self-reported data from our 2014 survey, from which we obtained a mean forest cover of 66% for a total participant farm's average land area of 79.3 ha (table 1, column 3).

Table 1 reports summary statistics for the intervention and the comparison groups in 2008, 2010, and 2014. The comparison group (column 4) includes small rural families that own less than 90 hectares on average and are representative of the colonist small farmers of the Transamazon highway (Moran 1981; Perz, Walker, and Caldas 2006; Börner et al. 2010). In 2010, these landowners devoted about 60% of their land to forest and about 30% to pasture. Most of the remaining land is dedicated to the cultivation of rice, cassava, or cocoa. While they derive income mainly from crops and livestock, other sources such as agricultural wage labor and government social programs, particularly *Bolsa Familia* and retirement pensions, are not negligible. Column 1 of table 1 gives weighted statistics for the intervention communities, taking into account that the participants represent no more than 10% of the household population in intervention communities.[4] Households in intervention communities do not differ much from households in comparison communities in terms of mean age (about 51 years), education (about 2.5 school years), family size (about 5 members), and pre-project deforestation: the share of forest cover decreased by 5% percentage points in both groups between 2008 and 2010. However, intervention communities start out with higher forest cover and lower pasture shares in total farmland, and higher wage revenues than comparison communities. The two groups also differ in land use changes over time, with less conversion from forest to pasture in the intervention communities between 2010 and 2014. Our goal is to assess the extent to which such changes can be attributed to the PAS project.

Empirical Strategy

Parameters of Interest

First and foremost, we aim to measure the impact of the project on forest conservation among participants. This impact is measured as the average amount of forestland saved by participating farmers as a result of the project. We chose to estimate effects on forest cover share because of the PES requirement that farmers under contract must maintain at least 50% of their landholdings under forest. We then also express our impact analysis in absolute hectares and in deforestation rates. Finally, we check for within-community spillover effects, that is, PAS-induced changes in the amount of forestland owned by non-participating farmers who reside in intervention communities.

To determine the average amount of forestland conserved among participants as a result of the PAS project, we need to calculate

[4] We assign to the participants a weight equal to 0.20 and to non-participants a weight equal to 1.76. These weights are obtained by dividing the population percentage by the corresponding sample percentage.

Table 1. Main Characteristics of Surveyed Farmers

Pre-treatment covariates	(1) Intervention (n=106) Mean	Std dev.	(2) Non-participants (n=54) Mean	Std dev.	(3) Participants (n=52) Mean	Std dev.	(4) Comparison (n=75) Mean	Std dev.	(5) ND before matching (3) v (4)	(6) Matched group Mean	Std dev.	(7) ND after matching (3) v (6)
Total land area in 2010 (ha)	110.78	*93.40*	114.48	*97.49*	77.56	*35.57*	88.34	*49.41*	–0.18	75.44	*22.04*	0.05
Forest cover in 2008 (% of land area)	73.20	*19.41*	72.92	*19.87*	75.74	*15.57*	67.27	*20.48*	0.33	75.76	*9.13*	0.00
Forest cover in 2010 (% of land area)	68.27	*17.99*	67.96	*18.27*	71.03	*15.92*	62.31	*20.56*	0.34	71.67	*9.44*	–0.03
Crop land in 2010 (% of land area)	8.06	*8.59*	7.97	*8.48*	8.85	*9.82*	6.35	*7.31*	0.20	6.82	*5.11*	0.18
Pasture land in 2010 (% of land area)	22.78	*18.51*	23.18	*18.94*	19.18	*14.62*	30.36	*20.21*	–0.45	20.74	*8.02*	–0.09
Crop value in 2010 (Reais)	8,828	*15,166*	9,128	*15,890*	6,136	*6,424*	5,299	*7,303*	0.09	4,715	*2,230*	0.21
Cattle value in 2010 (Reais)	17,356	*31,778*	18,432	*33,292*	7,688	*10,614*	14,399	*14,720*	–0.37	9,097	*5,649*	–0.12
Bolsa Familia in 2010 (Reais)	907	*1,749*	845	*1,682*	1,460	*2,248*	777	*772*	0.29	971	*423*	0.21
Retirement pension in 2010 (Reais)	1,694	*3,480*	1,733	*3,513*	1,348	*3,320*	2,690	*4,668*	–0.23	1,687	*1,891*	–0.09
Wage labor in 2010 (Reais)	1,842	*3,770*	1,493	*2,618*	4,978	*8,397*	1,270	*2,392*	0.42	3,146	*3,385*	0.20
Business in 2010 (Reais)	720	*3,334*	791.22	*3,519.87*	77.65	*482.36*	225	*876*	–0.15	94	*275*	–0.03
Education in 2010 (school years)	2.68	*2.64*	2.65	*2.61*	3.00	*2.97*	2.28	*2.20*	0.19	2.20	*1.02*	0.25
Age in 2010 (years)	51.30	*12.50*	51.65	*12.60*	48.17	*11.68*	50.92	*12.57*	–0.16	51.57	*6.53*	–0.25
Family members in 2010 (number)	4.90	*2.37*	4.83	*2.36*	5.48	*2.49*	4.83	*2.40*	0.19	5.63	*1.67*	–0.05
Post-treatment covariates												
Total land area in 2014 (ha)	108.57	*91.19*	111.83	*95.03*	79.28	*41.17*	88.62	*40.75*	–0.16	–	–	–
Forest cover in 2014 (% of land area)	61.05	*20.71*	60.50	*21.07*	65.93	*17.46*	52.61	*21.79*	0.48	–	–	–
Pasture land in 2014 (% of land area)	30.88	*21.90*	31.90	*22.26*	21.77	*17.02*	39.85	*21.24*	–0.66	–	–	–
Crop land in 2014 (% of land area)	7.32	*7.37*	7.10	*7.26*	9.34	*8.36*	6.46	*8.85*	0.24	–	–	–

Note: Intervention group (col. 1) refers to the 106 households living in the intervention communities. The group includes 54 non-participants (col. 2) and 52 participants (col. 3). Column 1 gives weighted statistics, taking into account that participants represent no more than 10% of the population in the real world. Comparison group (col. 4) refers to the 75 households living in the communities that were not offered the project. Column 5 gives the normalized difference (ND) in means between the participant and the comparison groups. Matched group (col. 6) refers to the households from the comparison group who were selected in the matching procedure using the 4-nearest neighbors in order to be compared to the participant group. Column 7 gives the normalized difference (ND) in means between the participant and the matched group.

the difference between the amount of forestland observed on participating farms in 2014 and the amount of forestland that would have been observed in those farms in 2014, had they not been involved in the project. This is the so-called average treatment effect on the treated (ATT), defined as ATT= $E(y^1 - y^0|D = 1)$, where y^1 denotes the amount of a farmer's forestland in the presence of the project, y^0 denotes the amount of a farmer's forestland in the absence of the project, and D is a dummy variable that takes on the value of one when the farmer participated in the project and zero otherwise. We use DID and DID-matching methods to estimate the outcome level in the unobserved state, namely $E(y^0|D = 1)$. We use households from the comparison communities to construct valid control groups. Those estimators allow us to take into account possible heterogeneous impacts among participants.

To understand which project components could be driving the observed impact, it is important to know which interventions participants were exposed to. As figure 1 shows, almost all beneficiaries of the PES component also participated in the information meetings and were registered under the CAR. However, most farmers in the comparison group were also in the process of registration under the CAR in 2014. Therefore, any land use impact of the project may be due to the meetings and PES components only. Similarly, IBAMA's command-and-control regulation affected all communities in the sample, whether intervention or control, since all were in blacklisted municipalities. Regarding the PES component, as mentioned earlier, the final survey was run just before the first contractual payment. Therefore, any impact of this component would be due to participants reducing deforestation activities according to their signed contracts, and in anticipation of the payments.

DID and DID-Matching Approaches

We first apply the DID treatment effect estimator by regressing Δy on D. The DID estimator is commonly used in evaluation work, and measures the impact of the program intervention by the difference in the before-after change in outcomes between participant and comparison groups (Todd 2007). Using DID requires a parallel trend assumption, which says that both groups follow the same trend during the pre-treatment period. In the present study, this assumption can be tested using a placebo test that applies the DID estimator to the change in the outcome over 2008–2010, when no effect should be detected.

As a robustness check, we then use various DID-matching estimators as well as linear models. Matching eliminates selection bias due to observable factors X by comparing treated farmers to observationally identical untreated ones (Imbens 2004). Moreover, the DID-matching estimator allows for temporally invariant differences in outcomes between participants and their X-matched untreated counterparts. Applied to our data, this identification strategy consists of comparing the change in participants' forest cover between 2010 and 2014 with the change in forest cover among matched untreated farmers from comparison communities. In addition to the parallel trend assumption, DID-matching requires a selection on observables assumption (Heckman and Robb 1985), which says that the dependence between treatment assignment and treatment-specific outcomes can be entirely removed by conditioning on observable variables. A crucial step to this end is thus to measure all factors, X, that are likely to drive both the decision to participate in the PAS project as well as decisions regarding the conservation of forestland.

It is important that the observable factors, X, are not affected by the project (Imbens 2004), which is why we use pre-treatment values from 2010 (and from 2008 when available). We include in the set of observable factors X extracted from the baseline 2010 survey: the total land area in hectares in 2010, the amount of forestland as a share of the total land area in 2010 and in 2008, the agricultural land as a share of the total land area in 2010, pastures as a share of the total land area in 2010, the market value of total agricultural production in 2010 (which includes sales and self-consumption), the market value of owned livestock in 2010, the amount of other sources of income received in 2010, such as those derived from wage labor, government social programs, retirement pensions, and outside businesses (in Reais), as well as family size and the age and education level (in school years) of the head of household.

Another key assumption for the validity of the DID-matching approach is that the treatment received by one farmer must not affect the outcome of another farmer. This assumption is referred to as the Stable-Unit-

Treatment-Value-Assumption (Rubin 1978). In our analysis, the validity of this assumption is not likely to be threatened because the connection between communities is extremely limited due to the poor quality of transportation infrastructure.

We use the nearest-neighbor matching estimator, which matches each participant to the two and four closest untreated farmers from the comparison communities, according to the vector X, and three different propensity score matching estimators applying the matching procedure to the summary statistic $\Pr(D_i = 1|X_i)$, the so-called propensity score (Abadie et al. 2004; Rosenbaum and Rubin 1983). We use the kernel-based propensity score matching estimator and the propensity score matching estimator using two or four matched observations as controls.

Further, we use the asymptotically-consistent estimator of the variance of the nearest-neighbor matching and propensity score matching estimators provided by Abadie and Imbens (2006). In addition, we test for the autocorrelation of the deforestation rates within communities and find that the size of the intra-cluster correlation for this variable is small (3.5%). This is not surprising, given that the farms are distant from each other, many households are recent migrants from different regions in Brazil, and there is no head of village and few associations. We thus choose to ignore the correlation at first and analyze the data in a standard way. As a robustness check, however, we compute some estimates for the clustered standard errors of the coefficients. For the DID estimates, we perform the wild cluster bootstrap-t procedure, as described by Cameron, Gelbach, and Miller (2008), taking the so-called communities as clusters. For DID-matching estimates, we bootstrap the standard error of the estimates. Our main results, albeit sometimes less precise, remain significant (see table A1 in the online supplementary appendix material).

Finally, we use another, computationally easier way to estimate the ATT, by regressing Δy on D, controlling for the propensity score (or for X). We run these linear regressions as a robustness check. Just as in the DID regression, we provide heteroskedasticity-consistent standard errors.

Results of the Impact Evaluation

We first apply the DID estimator to our data to estimate the average effect of the PAS project on the forest cover of participant and non-participant households in intervention communities. We obtain a positive point estimate (ATT equals 3.29 points of percentage), but this result lacks precision (robust standard error equals 2.74, meaning that we fail to reject the null of no impact). To further study the likely effects of PAS, we thus turn to the subset of households who chose to participate in the project.

Project Enrollment

The proponent first offered the project to the 350 households who previously participated in Proambiente, which explains why 80% of PAS participants also participated in this previous program. The reason that 20% of the previous participants in Proambiente did not enroll in the PAS project is unclear: some might have moved away, while others might have been disappointed by the early suspension of Proambiente, or perhaps considered that the PES compensation was an insufficient incentive. This enrolment process might have led to a particular profile of participants. We thus start our analysis by comparing participating and non-participating households (living in intervention communities). As shown in table 1, participants (column 3) did not differ significantly from non-participants in terms of the share of forest cover (about 75% of the land area in 2008 and 70% in 2010), cropland (about 8%), or pasture land (around 20%). However, participating households on average had smaller plots, owned less livestock, and earned more money from wage labor (e.g., agricultural labor) than non-participating households (column 2) before the start of the project. These features will thus play a central role in the matching procedure that follows.

Impacts on Participants' Forest Cover

Comparing participants to the comparison group in 2014, one can observe that participants have much higher forest cover—about 13 percentage points more. This difference obviously cannot be interpreted as the ATT, since participants already had higher forest cover before the start of the project. To estimate the ATT, we apply the aforementioned estimators to the group of participants using the comparison group to estimate the counterfactual level of forest cover. Applying the DID-estimator only requires testing the parallel trend assumption. Moreover, applying the

DID-matching estimators requires computing propensity scores and determining whether the matching procedure performed well.

We start by computing conditional probabilities for being enrolled in the project (or propensity scores) by estimating a probit model where the dependent variable is D and which includes all of the aforementioned pre-treatment covariates X presented in table 1. Figure A2 in the online supplementary appendix material shows that densities in both groups are high enough for a wide range of propensity scores, meaning that the matching procedure is likely to perform well.

We then compare the extent of balancing between the participant and comparison groups before and after the matching procedure. We calculate the normalized difference between these two groups for the pre-treatment covariates X. The normalized difference is the difference in means divided by the square root of the sum of variances for both groups, and is the most commonly accepted diagnostic used to assess covariate balance (Rosenbaum and Rubin 1985; Stuart 2010). The normalized difference is considered negligible when it is below the suggested rule of thumb of 0.25 standard deviations (Rubin 2001; Imbens and Wooldridge 2009). Column 5 of table 1 shows that, before matching, the participant group (column 3) differs significantly from the comparison group (column 4) in terms of land use (notably forest cover and pasture land) and wage income. Column 7 of table 1 reports the normalized mean differences between participants and the constructed matched group (column 6). All normalized differences are below 0.25 standard deviations, which indicates that the matching procedure was successful in constructing a valid control group.

We then examine the validity of the parallel trends assumption by running a placebo test that applies the identification strategy to the pre-treatment period of 2008–2010. As shown in table A2 in the online supplementary appendix material, we find no significant difference in forest cover between households enrolled in the project and households living in comparison communities; we also do not find any significant difference between participants and their matched counterparts. These results indicate that the three groups (participants, comparison and matched) followed the same trend before the project start, which supports our identification strategy, whether it is the DID or the DID-matching approach. In our sample, almost 80% of the participants in the PAS project had previously participated in the Proambiente project. Although previous participation in the Proambiente project explains participation in the PAS project, it does not translate to any difference in deforestation rates between groups in the absence of the project, as shown by the parallel trends before 2010. We can thus safely assume that participation in the Proambiente project is not a confounding variable in our framework.

The main results of the study—the effects of the program among participants—are presented in table 2. Column 1 gives the estimates of the impact of the project on forestland. In the majority of cases, the impact is estimated with precision. Using the smallest significant impact estimator, which is the DID estimator, the ATT equals 5.41 percentage points. The ATT represents the difference in 2014 between the average land area devoted to forests among participant farmers (65.93%) and the average land area they would have devoted to forests had they not participated. Given that the average land area in participating farms equals 79.28 hectares, an average of approximately 4.3 hectares of forests was saved on each participating farm compared to the counterfactual scenario of no project.

This result is shown graphically in figure 2. We observe that the amount of forest cover continues to decline in both participant and control groups after 2010. However, we see a clear break in the deforestation trend among participants, which we can attribute to the PAS project. After 2010, the deforestation rate among participants decreased to 1.8%, which means that the project led to an approximately 50% decrease in the average deforestation rate in these farms compared to the counterfactual deforestation rate, which is around 4% in 2014. Finally, figure 2 shows that the average landowner from comparison communities nearly reached the threshold of 50% of land as Legal Reserve in 2014, and that the average PAS participant would have crossed this threshold in just a few years without the project.

Impacts on Livelihoods Portfolio

We then apply our identification strategy to the total land area to check whether any change should be detected and attributed to the project. We did this because one might expect that participants have increased the total land area to comply with the requirements of the project while clearing the same area of forest as those

Table 2. Impact on Participants in 2014

Estimator	(1) Forest cover (%)	(2) Total land (ha)	(3) Crop land (%)	(4) Pastures (%)
DID	5.41**	1.44	0.38	−6.91**
	2.71	*5.72*	*1.58*	*2.74*
DID-matching				
NNM(4X)	7.10**	−4.29	−0.50	−8.11***
	3.21	*7.17*	*2.46*	*3.07*
NNM(2X)	10.66**	5.43	−1.80	−9.95**
	4.99	*8.43*	2.81	*4.31*
PSM (kernel)	7.98*	−2.28	1.39	−11.32***
	4.52	*5.66*	*4.62*	*3.25*
PSM(2N)	8.61**	−1.50	*1.50*	−11.70***
	4.16	*4.60*	*3.69*	*1.67*
PSM(4N)	7.38*	−6.79	*0.37*	−9.39***
	4.49	*6.44*	*3.67*	*1.73*
Linear regression				
OLS(X)	6.22*	−0.73	1.14	−7.82***
	3.23	*5.98*	*1.91*	*2.97*
OLS(PS)	6.06°	−0.26	0.54	−7.15**
	3.91	*6.07*	*2.82*	*3.35*
Mean value y_1	65.93	79.28	9.34	21.77

Note: This table displays the average treatment effect on the treated, where the treated group refers to the participant group. Mean value y_1 is the mean value of the outcome in 2014 in the treated group. Forest cover, cropland, and pasture are expressed as a share of the total land area. The total land area is expressed in hectares. Asterisks ***, **, and *, as well as ° denote rejection of the null hypothesis of no impact at the 1%, 5%, 10%, and 15% significance levels, respectively. DID refers to the Difference-in-Differences estimator. NNM(4X) (resp.2X) refers to the nearest neighbor estimator using 4 (resp. 2) matched observations as controls. PSM (kernel) refers to the kernel-based propensity score matching estimator. PSM(2N) (4N) refers to the propensity score matching estimator using 2 (4) matched observations as controls. OLS(X) refers to the linear regression using ordinary least squares and controlling for *X*, and OLS(PS) refers to the linear regression using ordinary least squares and controlling for the propensity score. Standard errors are in italics below coefficients.

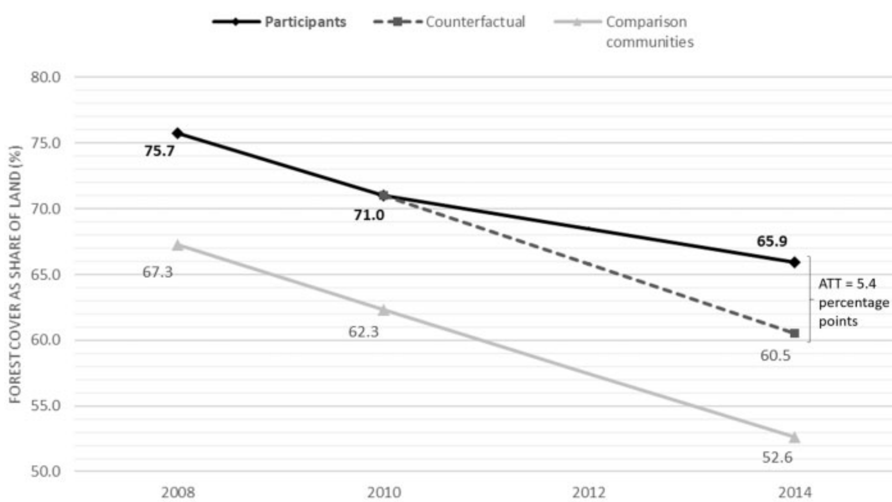

Figure 2. Forest cover as a share of land among participants

Note: This figure provides an illustration of the parallel trend assumption, as well as a representation of the DID estimator of the impact. It depicts the mean value of the forest cover in the group of participants (52 households) and in the comparison group (75 households), in 2008, 2010, and 2014, as well as the DID-estimate of the participants' forest cover in 2014, had they not been participants (the counterfactual value)

in the control group. We find no difference between participant and control groups in 2014 (see column 2 of table 2). We conclude that less deforestation among participants necessarily caused some changes to the way that other owned land is used. We thus apply our identification strategy to the proportion of land devoted to crops and pastures. We find no evidence of any impacts on cropland (see column 3 of table 2). In contrast, we do find evidence that the project had a significant impact on the creation of pastures. Column 5 of table 2 displays the estimates of the impact of the project on participants in terms of amount of total land as pasture. Using the smallest significant impact estimator, which is the DID estimator, the ATT equals -6.91 percentage points. This means that the creation of an average of 5.5 hectares of pastures have been avoided in each participating farm compared to a scenario without the PAS project. These results fit well with our estimates of the project's impact on forest cover. We thus conclude that an average of about 4 to 5 hectares of forest have been saved on each participating farm in 2014, and that this conservation came at the expense of pastures rather than cropland.

Since participants did not receive the PES component until 2014, we investigate whether the changes in land use that occurred due to the project, that is, more forests and less pastures, prompted participating farmers to seek alternative sources of income outside the farm. To do so, we apply our identification strategy to the variable that measured wage labor in 2014. Most estimators do not allow us to reject the null hypothesis of no impact (see column 1 of table A3 in the online supplementary appendix material). Thus, we are not able to conclude that participants sought new sources of income outside the farm at this stage of the project.

Finally, we apply our identification strategy to a cattle ranching intensification variable, constructed as the ratio of the value of livestock to pasture area.[5] The point estimate is positive but lacks precision, and most of the time we are not able to reject the null hypothesis of no impact (see column 2 of table A3 in the online supplementary appendix material). Thus, our data do not allow us to determine whether the participants in the project compensated for forest conservation by intensifying their livestock operations as a result of the project.

Looking at the participant group, we can thus safely conclude that the PAS project had a significant impact on forest cover by curbing deforestation, and that this change occurred to the detriment of new pastures, not cropland. On the contrary, we failed to detect any significant impact on other variables like livestock or wage labor outside the farm.

Assessing Spillovers

We now test for the presence of spillover effects within intervention communities by applying the DID and DID-matching estimators to the non-participants living in these communities. Again, we compute conditional probabilities for this group (see the distribution of propensity scores in figure A3 in the online supplementary appendix material). We run the placebo test and conclude that our identification strategy is also valid for this group (see column 2 in table A2 in the online supplementary appendix material). We also run balancing tests before and after the matching procedure and conclude that it performs well (see table A4 in the online supplementary appendix material). Column 1 of table A5 in the online supplementary appendix material shows the estimates of the impact of the project on the forest cover of this group. The null assumption of no impact cannot be rejected whatever the estimator considered, which indicates that, if there is any spillover effect, it is too small to be detected using our data (see figure A4 in the online supplementary appendix material). We also do not find any significant impact on pastures (column 2), cropland (column 3) or total land area (column 4).

We also examine spillover effects of the project to comparison communities, which was another possible form of leakage. It seems unlikely that comparison communities faced higher compensatory demand for beef, because cattle production did not decrease significantly in intervention communities because of the project. Moreover, most of the crop and small livestock production in our sample is for subsistence use. Beef and cocoa are the only products that are sold by a relatively important share of the sample, with around one third of the sample selling cattle in 2010 (10 heads of livestock sold on average), and 44% selling cocoa (1.7 ton of cocoa per seller on average). However, the quantities sold remain negligible compared to the total production of beef (616,404 heads) and cocoa (3,191 tons) registered by the Brazilian Institute of Geography and Statistics (IBGE) in 2010 for the three municipalities covered by the study. Thus, even large changes in the

[5] The average value of all cattle owned by participants in 2014 is about 15,000 Reais, which corresponds to about 15 cows per farm. In 2010, participants owned an average of about 11 cows per farm.

production of the 350 participants in the project would have a negligible impact on the local market.

Costs of Avoided CO_2 Emissions

We take our main estimate of the impact of the project on participants as a starting point for calculating the averted CO_2 emissions generated by the project. Given that sampled participants saved an average of approximately 4.3 ha of forest on their farm since the beginning of the project in 2012, we scale up this point estimate to the 350 households involved in the project, assessing that a total of 1,505 hectares of forest were saved as a result of the project.

Similar to Jayachandran et al. (2017), we use satellite-based estimates of biomass in forests, available at a 30-meter resolution and provided by the World Resources Institute to estimate the carbon in forestland in our study area; the average is 116 tons of carbon per hectare of forest with at least 50% tree cover. We then calculate the impact of the forestland conserved in tons of CO_2 (tCO_2; 1 $tC=3.67$ tCO_2), and determine that the PAS project led to 639,080 tCO_2 in avoided emissions (1,826 tCO_2 per participant) over two years.[6]

The total costs of the PAS project can be estimated using the amount of PES disbursed to participants in 2014 ($626 per participant, which leads to a total of $219,100), plus start-up as well as operational costs (the total costs then reach $538,300, i.e., $1,538 per participant over two years). We estimate these costs using information on project implementation costs provided by Sills et al. (2014). This amount is an estimate of the annual costs of the project, based on the total budget provided by IPAM for the five years of the project. More than half of the costs are dedicated to community development (54%, including PES, inputs, and technical assistance) while finance and administration represent the second-most important item (19%), followed by policy and planning activities (10%), education and communication (6%), and others (methods development; measurement, reporting and verification; 5%). Over the first two years of the project, the total cost of the project is thus $0.84 per tCO_2 emissions avoided. This number is nearly twice that estimated by Jayachandran et al. (2017) in Uganda ($0.46 per tCO_2), which may be due to a higher focus on technical assistance in the PAS project, and to relatively high costs in Brazil.

Conclusion

Subnational REDD+ initiatives have emerged in many areas around the world, and particularly in Brazil. However, the impacts of these projects and programs have been largely under-studied. This article addresses this gap by providing a robust impact assessment of a REDD+ pilot project that offers a PES scheme, along with technical and administrative support, to facilitate farmer compliance with the Forest Code in the Brazilian Amazon. Our main result (a 50% decrease in deforestation rates) suggests that REDD+ projects that use a mix of interventions—including incentives, disincentives, and enabling measures—may constitute a promising strategy to reduce deforestation rates among small Amazonian landowners. The long term on-the-ground presence of the project proponent and the context of gradual implementation of command-and-control measures in the most remote areas probably helped to obtain such encouraging results. It should be noted, however, that at the time of data collection the PAS project was still in the early stages of implementation, and our data do not allow us to determine whether participants will be able to eliminate their reliance on deforestation activities altogether by switching towards more sustainable agricultural production systems before the project's expiration date. Our results indicate that project participants were able to reduce their deforestation activities by devoting less pasture land to their cattle in the first year of the project, and that they may not have reduced their agricultural activity as a result of less deforestation.

These results raise several questions. Will participating farmers adopt more intensive

[6] This estimate does not take into account potential reductions in methane emissions, as we were not able to demonstrate a significant impact of the project on cattle ranching activities. Following the Tier 1 methodology provided by the Intergovernmental Panel on Climate Change, we assume that the biomass after conversion from forest to pasture is zero (Verchot et al. 2006). Moreover, as the literature on conversion from forestland to grassland in the tropics provides evidence for net gains as well as net losses in soil carbon (Verchot et al. 2006), we do not consider this component either.

cattle ranching systems in the long run? As extensive cattle ranching is a major driver of deforestation in the study area, livestock intensification appears to be a promising strategy to reduce deforestation and constitutes one of IPAM's priorities, but may face some limits if deforestation is to be further reduced. Are there other strategies available to farmers that would enable them to reduce their dependence on deforestation activities? Among the possible alternative practices, the expansion of cocoa production could be a promising alternative to cattle ranching and swidden agriculture, because cocoa is grown in agroforestry systems (as such, it can be recognized as Legal Reserve) and has the potential to be more profitable than extensive cattle ranching (Sablayrolles, Oliveria, and Pinto 2012; Schneider et al. 2015). A limitation, however, is that cocoa production requires fertile soils, high start-up costs, and technical agricultural support to obtain good quality cocoa. Towards this end, the PAS project includes provisions aimed at providing technical assistance and farm inputs for the adoption of such sustainable practices. An evaluation of the project over the long-term could help assess participants' ability to eliminate their dependence on the deforestation of mature forest, switch toward more sustainable agricultural production systems, and enhance their subsistence livelihoods. Understanding the effectiveness of direct cash payments on smallholders' conservation decisions in the context of their broader strategies is indeed fundamental to understanding the implications of PES-based REDD+ initiatives in the long run.

Supplementary Material

Supplementary material are available at *American Journal of Agricultural Economics* online.

References

Abadie, A., D. Drukker, J.L. Herr, and G.W. Imbens. 2004. Implementing Matching Estimators for Average Treatment Effects in Stata. *Stata Journal* 4: 290–311.

Abadie, A., and G.W. Imbens. 2006. Large Sample Properties of Matching Estimators for Average Treatment Effects. *Econometrica* 74: 235–67.

Alix-Garcia, J., C. McIntosh, K.R.E. Sims, and J.R. Welch. 2013. The Ecological Footprint of Poverty Alleviation: Evidence from Mexico's Oportunidades Program. *Review of Economics and Statistics* 95: 417–35.

Alix-Garcia, J., and H. Wolff. 2014. Payment for Ecosystem Services from Forests. *Annual Review of Resource Economics* 6: 361–80.

Alix-Garcia, J.M., E.N. Shapiro, and K.R.E. Sims. 2012. Forest Conservation and Slippage: Evidence from Mexico's National Payments for Ecosystem Services Program. *Land Economics* 88: 613–38.

Alix-Garcia, J.M., K.R.E. Sims, and P. Yañez-Pagans. 2015. Only One Tree from Each Seed? Environmental Effectiveness and Poverty Alleviation in Mexico's Payments for Ecosystem Services Program. *American Economic Journal: Economic Policy* 7: 1–40.

Arriagada, R.A., P.J. Ferraro, E.O. Sills, S.K. Pattanayak, and S. Cordero-Sancho. 2012. Do Payments for Environmental Services Affect Forest Cover? A Farm-Level Evaluation from Costa Rica. *Land Economics* 88: 382–99.

Assunção, J., and R. Rocha. 2014. Getting Greener by Going Black: The Priority Municipalities in Brazil. Rio de Janeiro, Brazil: Climate Policy Initiative.

Atela, J.O., P.A. Minang, C.H. Quinn, and L.A. Duguma. 2015. Implementing REDD+ at the Local Level: Assessing the Key Enablers for Credible Mitigation and Sustainable Livelihood Outcomes. *Journal of Environmental Management* 157: 238–49.

Athey, S., and G. Imbens. 2017. The State of Applied Econometrics-Causality and Policy Evaluation. *Journal of Economic Perspectives* 31 (2): 3–32.

Azevedo, A.A., R. Rajão, M.A. Costa, M.C.C. Stabile, M.N. Macedo, T.N.P. dos Reis, A. Alencar, B.S. Soares-Filho, and R. Pacheco. 2017. Limits of Brazil's Forest Code as a Means to End Illegal Deforestation. *Proceedings of the National Academy of Sciences* 114: 7653–8.

Bartels, W.L., M. Schmink, E.A. Borges, A.P. Duarte, and H.D.S dos Santos Arcos. 2010. Diversifying Livelihoods Systems, Strenghtening Social Networks and Rewarding Environmental Stewardship

Among Small-scale Producers in the Brazilian Amzaon: Lessons from Proambiente. In *Payments for Environmental Services, Forest Conservation and Climate Change: Livelihood in the REDD?* ed. L. Tacconi, S. Mahanty, and H. Suich. 82–105. Cheltenham, UK: Edward Elgar Publishing Limited.

Börner, J., K. Baylis, E. Corbera, D. Ezzine-de Blas, P.J. Ferraro, J. Honey-Rosés, R. Lapeyre, M. Persson, and S. Wunder. 2016. Emerging Evidence on the Effectiveness of Tropical Forest Conservation. *PLoS One* 11: e0159152.

Börner, J., K. Baylis, E. Corbera, D. Ezzine-de Blas, J. Honey-Rosés, U.M. Persson, and S. Wunder. 2017. The Effectiveness of Payments for Environmental Services. *World Development* 96: 359–74.

Börner, J., E. Marinho, and S. Wunder. 2015. Mixing Carrots and Sticks to Conserve Forests in the Brazilian Amazon: A Spatial Probabilistic Modeling Approach. *PLoS One* 10: e0116846.

Börner, J., S. Wunder, F. Reimer, R.K. Bakkegaard, V. Viana, J. Tezza, T. Pinto, L. Lima, and S. Marostica. 2013. *Promoting Forest Stewardship in the Bolsa Floresta Programme: Local Livelihood Strategies and Preliminary Impacts*. Rio de Janeiro, Brazil: Center for International Forestry Research (CIFOR). Manaus, Brazil: Fundação Amazonas Sustentável(FAS). Bonn, Germany: Zentrum für Entwicklungsforschung (ZEF), University of Bonn.

Börner, J., S. Wunder, S. Wertz-Kanounnikoff, M.R. Tito, L. Pereira, and N. Nascimento. 2010. Direct Conservation Payments in the Brazilian Amazon: Scope and Equity Implications. *Ecological Economics* 69: 1272–82.

Bos, A., A. Duchelle, A. Angelsen, V. Avitabile, V. De Sy, M. Herold, S. Joseph, et al. 2017. Comparing Methods for Assessing the Effectiveness of Subnational REDD+ Initiatives. *Environmental Review Letters* 12(7): 074007.

Brandon, A., P.J. Ferraro, J.A. List, R.D. Metcalfe, M.K. Price, and F. Rundhammer. 2017. Do the Effects of Social Nudges Persist? Theory and Evidence from 38 Natural Field Experiments. Working Paper, National Bureau of Economic Research 23277.

Brimont, L., D. Ezzine de Blas, A. Karsenty, and A. Toulon. 2015. Achieving Conservation and Equity Amidst Extreme Poverty and Climate Risk: The Makira REDD+ Project in Madagascar. *Forest* 6(3): 748–768.

Cameron, A.C., J.B. Gelbach, and D.L. Miller. 2008. Bootstrap-Based Improvements for Inference with Clustered Errors. *Review of Economics and Statistics* 90: 414–27.

Chhatre, A., and A. Agrawal. 2009. Trade-offs and Synergies between Carbon Storage and Livelihood Benefits from Forest Commons. *Proceedings of the National Academy of Sciences* 106: 17667–70.

Cisneros, E., S.L. Zhou, and J. Börner. 2015. Naming and Shaming for Conservation: Evidence from the Brazilian Amazon. *PLoS One* 10: e0136402.

Costedoat, S., E. Corbera, D. Ezzine-de Blas, J. Honey-Rosés, K. Baylis, and M.A. Castillo-Santiago. 2015. How Effective Are Biodiversity Conservation Payments in Mexico? *PLoS One* 10: e0119881.

Duchelle, A., C. de Sassi, P. Jagger, M. Cromberg, A. Larson, W. Sunderlin, S. Atmadja, I.A.P. Resosudarmo, and C.D. Pratama. 2017. Balancing Carrots and Sticks in REDD+: Implications for Social Safeguards. *Ecology and Society* 22(3): 2. https://doi.org/10.5751/ES-09334-220302.

Duchelle, A.E., M. Cromberg, M.F. Gebara, R. Guerra, T. Melo, A. Larson, P. Cronkleton, et al. 2014a. Linking Forest Tenure Reform, Environmental Compliance, and Incentives: Lessons from REDD+ Initiatives in the Brazilian Amazon. *World Development* 55: 53–67.

Duchelle, A.E., M. Greenleaf, D. Mello, M.F. Gebara, and T. Melo. 2014b. Acres State System of Incentives for Environmental Services (SISA), Brazil. In *REDD+ on the Ground: A Case Book of Subnational Initiatives across the Globe*, ed. Sills, E. O., Atmadja, S. S., de Sassi, C., Duchelle, A. E., Kweka, D. L., Resosudarmo, I. A. P., and Sunderlin, W. D. Bogor, Indonesia: Center for International Forestry Research (CIFOR), pp. 33–50.

Dyer, G.A., R. Matthews, P. Meyfroidt, and R. Huerta-Quintanilla. 2012. Is There an Ideal REDD+ Program? An Analysis of

Policy Trade-offs at the Local Level. *PLoS One* 7: e52478.

Ezzine-de-Blas, D., J. Börner, A.L. Violato-Espada, N. Nascimento, and M.G. Piketty. 2011. Forest Loss and Management in Land Reform Settlements: Implications for REDD Governance in the Brazilian Amazon. *Environmental Science & Policy* 14: 188–200.

Ezzine-de Blas, D., E. Corbera, and R. Lapeyre. 2015. Crowding-in or Crowding-out? A Conceptual Framework to Understand Motivations in Payments for Ecosystem Services. In *Conference Paper Resource Politics 2015 Institute of Development Studies.*

Food and Agricultural Organization of the United Nations. 2015. Global Forest Resource Assessment 2015. Report, Rome.

Garbach, K., M. Lubell, and F.A. DeClerck. 2012. Payment for Ecosystem Services: The Roles of Positive Incentives and Information Sharing in Stimulating Adoption of Silvopastoral Conservation Practices. *Agriculture, Ecosystems & Environment* 156: 27–36.

Gebara, M.F., L. Fatorelli, P. May, and S. Zhang. 2014. REDD+ Policy Networks in Brazil: Constraints and Opportunities for Successful Policy Making. *Ecology and Society* 19(3): 53.

Gebara, M.F., and A. Thault. 2013. GHG Mitigation in Brazil's Land Use Sector: An Introduction to the Current National Policy Landscape. Washington DC: WRI.

Godar, J., T.A. Gardner, E.J. Tizado, and P. Pacheco. 2014. Actor-specific Contributions to the Deforestation Slowdown in the Brazilian Amazon. *Proceedings of the National Academy of Sciences* 111: 15591–6.

Grace, J., E. Mitchard, and E. Gloor. 2014. Perturbations in the Carbon Budget of the Tropics. *Global Change Biology* 20: 3238–55.

Hansen, M.C., P.V. Potapov, R. Moore, M. Hancher, S.A. Turubanova, A. Tyukavina, D. Thau, et al. 2013. High-Resolution Global Maps of 21st-Century Forest Cover Change. *Science* 342: 850–3.

Harris, N.L., S. Brown, S.C. Hagen, S.S. Saatchi, S. Petrova, W. Salas, M.C. Hansen, P.V. Potapov, and A. Lotsch. 2012. Baseline Map of Carbon Emissions from Deforestation in Tropical Regions. *Science* 336: 1573–6.

Heckman, J.J., and R. Robb. 1985. Alternative Methods for Evaluating the Impact of Interventions: An Overview. *Journal of Econometrics* 30: 239–67.

Honey-Roses, J., K. Baylis, and M.I. Ramirez. 2011. A Spatially Explicit Estimate of Avoided Forest Loss. *Conservation Biology* 25: 1032–43.

Imbens, G.W. 2004. Nonparametric Estimation of Average Treatment Effects under Exogeneity: A Review. *Review of Economics and Statistics* 86: 4–29.

Imbens, G.W., and J.M. Wooldridge. 2009. Recent Developments in the Econometrics of Program Evaluation. *Journal of Economic Literature* 47: 5–86.

Jayachandran, S., J. de Laat, E.F. Lambin, C.Y. Stanton, R. Audy, and N.E. Thomas. 2017. Cash for Carbon: A Randomized Trial of Payments for Ecosystem Services to Reduce Deforestation. *Science* 357: 267–73.

Moran, E.F. 1981. *Developing the Amazon*. Bloomington, USA: Indiana Univ. Press.

Nepstad, D., D. McGrath, C. Stickler, A. Alencar, A. Azevedo, B. Swette, T. Bezerra et al. 2014. Slowing Amazon Deforestation through Public Policy and Interventions in Beef and Soy Supply Chains. *Science* 344: 1118–23.

Pattanayak, S.K., S. Wunder, and P.J. Ferraro. 2010. Show Me the Money: Do Payments Supply Environmental Services in Developing Countries? *Review of Environmental Economics and Policy* 4: 254–74.

Persson, U.M., and F. Alpizar. 2013. Conditional Cash Transfers and Payments for Environmental Services Conceptual Framework for Explaining and Judging Differences in Outcomes. *World Development* 43: 124–37.

Perz, S.G., R.T. Walker, and M.M. Caldas. 2006. Beyond Population and Environment: Household Demographic Life Cycles and Land Use Allocation among Small Farms in the Amazon. *Human Ecology* 34: 829–49.

Pinto de Paulo Pedro, E. 2016. O papel do Pagamento por Serviços Ambientais conforme a realidade de diferentes Perfis de Agricultores familiar da Amazônia. MS Thesis, University of Brasilia, Center for sustainable development.

Puyravaud, J.P. 2003. Standardizing the Calculation of the Annual Rate of Deforestation. *Forest Ecology and Management* 177: 593–6.

Robalino, J., and A. Pfaff. 2013. Ecopayments and Deforestation in Costa Rica: A Nationwide Analysis of PSA's Initial Years. *Land Economics* 89: 432–48.

Rosenbaum, P.R., and D.B. Rubin. 1983. The Central Role of the Propensity Score in Observational Studies for Causal Effects. *Biometrika* 70: 41–55.

———. 1985. Constructing a Control Group Using Multivariate Matched Sampling Methods That Incorporate the Propensity Score. *American Statistician* 39: 33–8.

Rubin, D.B. 1978. Bayesian Inference for Causal Effects: The Role of Randomization. *Annals of Statistics* 6: 34–58.

———. 2001. Using Propensity Scores to Help Design Observational Studies: Application to the Tobacco Litigation. *Health Services and Outcomes Research Methodology* 2: 169–88.

Sablayrolles, P., C. Oliveria, and C. Pinto. 2012. Adequação ambiental e políticas públicas para a agricultura familiar do Alto Xingu. Associação para o Desenvolvimento da Agricultura Familiar do.

Samii, C., M. Lisiecki, P. Kulkarni, L. Paler, and L. Chavis. 2014. Effects of Payment for Environmental Services (PES) on Deforestation and Poverty in Low and Middle Income Countries: A Systematic Review. *Campbell Systematic Reviews* 11.

Sánchez-Azolfeifa, G.A., A. Pfaff, J.A. Robalino, and J.P. Boomhower. 2007. Costa Rica's Payment for Environmental Services Program: Intention, Implementation, and Impact. *Conservation Biology* 21: 1165–73.

Schneider, C., E. Coudel, F. Cammelli, and P. Sablayrolles. 2015. Small-Scale Farmers' Needs to End Deforestation: Insights for REDD+ in São Felix do Xingu (Pará, Brazil). *International Forestry Review* 17: 124–42.

Scullion, J., C.W. Thomas, K.A. Vogt, O. Pérez-Maqueo, and M.G. Logsdon. 2011. Evaluating the Environmental Impact of Payments for Ecosystem Services in Coatepec (Mexico) Using Remote Sensing and On-site Interviews. *Environmental Conservation* 38: 426–34.

Sharma, B., P. Shyamsundar, M. Nepal, S. Pattanayak, and B. Karky. 2017. Costs, Cobenefits, and Community Responses to REDD+: A Case Study from Nepal. *Ecology and Society* 22(2): 34.

Sills, E.O., S.S. Atmadja, C. de Sassi, A.E. Duchelle, D.L. Kweka, I.A.P. Resosudarmo, and W.D. Sunderlin, (eds). 2014. *REDD+ on the Ground: A Case Book of Subnational Initiatives across the Globe*, Bogor, Indonesia: CIFOR.

Simonet, G., A. Karsenty, C. de Perthuis, P. Newton, and B. Schaap. 2014. REDD+ Projects in 2014: An Overview Based on a New Database and Typology. *Cahiers de la Chaire Economie du Climat—Information and Debates Series* 32.

Sims, K., J. Alix-Garcia, E. Shapiro-Garza, L. Fine, V. Radeloff, G. Aronson, S. Castillo, C. Ramirez-Reyes, and P. Yañez-Pagans. 2014. Improving Environmental and Social Targeting through Adaptive Management in Mexico's Payments for Hydrological Services Program. *Conservation Biology* 28: 1151–9.

Smith, N.J., I.C. Falesi, P.D.T. Alvim, and E.A.S. Serrao. 1996. Agroforestry Trajectories among Smallholders in the Brazilian Amazon: Innovation and Resiliency in Pioneer and Older Settled Areas. *Ecological Economics* 18: 15–27.

Soares-Filho, B.S., D.C. Nepstad, L.M. Curran, G.C. Cerqueira, R.A. Garcia, C.A. Ramos, E. Voll, A. McDonald, P. Lefebvre, and P. Schlesinger. 2006. Modelling Conservation in the Amazon Basin. *Nature* 440: 520–3.

Stuart, E.A. 2010. Matching Methods for Causal Inference: A Review and a Look Forward. *Statistical Science* 25: 1–21.

Sunderlin, W.D., A.M. Larson, A. Duchelle, E.O. Sills, C. Luttrell, P. Jagger, S. Pattanayak, P. Cronkleton, and A.D. Ekaputri. (2010). Technical guidelines for research on REDD+ project sites with survey instruments and code book. CIFOR.

Sunderlin, W.D., and E.O. Sills. 2012. REDD+ Projects as a Hybrid of Old and New Forest Conservation Approaches. *Analysing REDD*, ed. Angelsen, A., Brockhaus, M., Sunderlin, W. D., and Verchot, L. V. p. 211. Bogor, Indonesia: CIFOR.

Temu, B., J. Abdallah, J. Kessy, and G. Monela. 2015. Carbon Business Scenarios and Communities Choices under REDD+ in Lindi Rural District, Tanzania. *International Journal of Ecological Economics and Statistics* 36: 47–63.

Todd, P.E. 2007. Chapter 60 Evaluating Social Programs with Endogenous Program Placement and Selection of the Treated. In *Handbook of Development Economics*, vol. 4, ed. T.P. Schultz and J.A. Strauss, 3847–94. Amsterdam, The Netherlands: North-Holland.

Verchot, L., K.T.R. Lasco, S. Ogle, J. Raison, Y. Li, D. Martino, B. McConkey, and P. Smith. 2006. 2006 IPCC Guidelines for National Greenhouse Gas Inventories, Chapter 6 Grassland. Intergovernmental Panel on Climate Change, vol. 4: Agriculture, Forestry and Other Land Use.

Viana, V., J. Tezza, V. Solidade, S. Marostica, V. Salviati, and A. Soares. 2013. Impactos do Programa Bolsa Floresta: uma avaliação preliminar. *Inclusão Social* 6.

Wunder, S. 2007. The Efficiency of Payments for Environmental Services in Tropical Conservation. *Conservation Biology* 21: 48–58.